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Spatial Interaction Filters for Monitoring Harmful Algae Blooms

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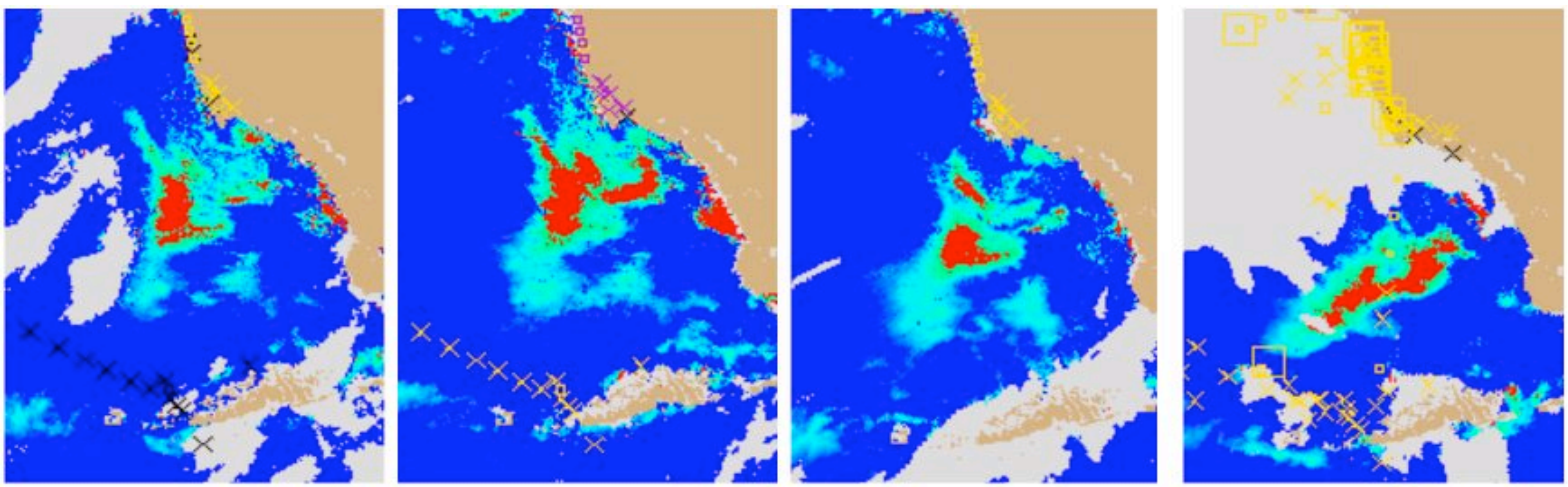
Background

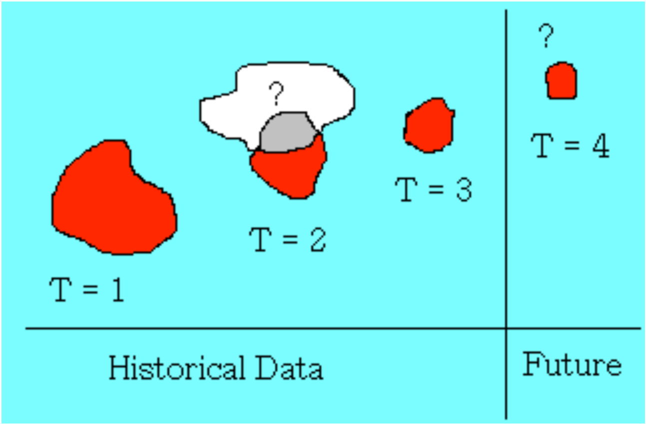
Tracking and predicting the movement of ocean objects are essential to oceanographic studies. The prevailing manual processes are time-consuming and less efficient.



Images above show a harmful algae bloom (HAB), highlighted as chlorophyll anomaly, drifting along the southwest Florida coast in December 2001.

Problem

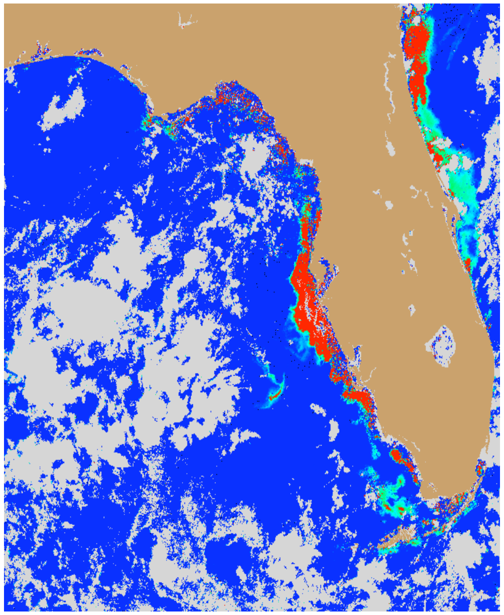
Given an anomaly object in an image sequence (t=1,..,n), find the object at t=n+1...



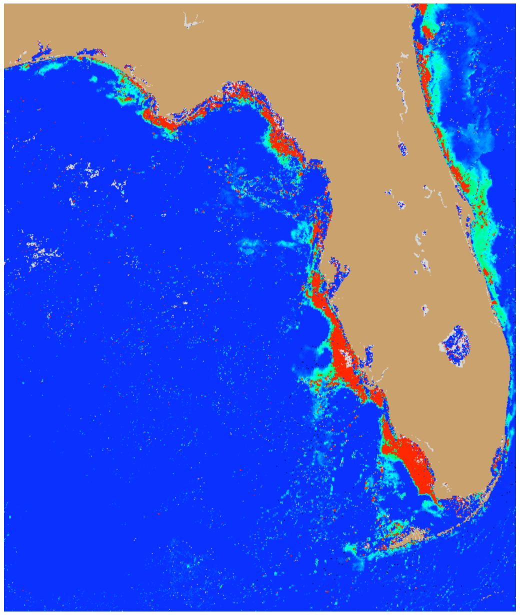
- spatiotemporal modeling (shape & time)
- missing data (80% clouds in images)
- knowledge based process

Missing Data Recovery

Linear interpolation is used to recover the missing data under the clouds.



Anomaly data with cloud.

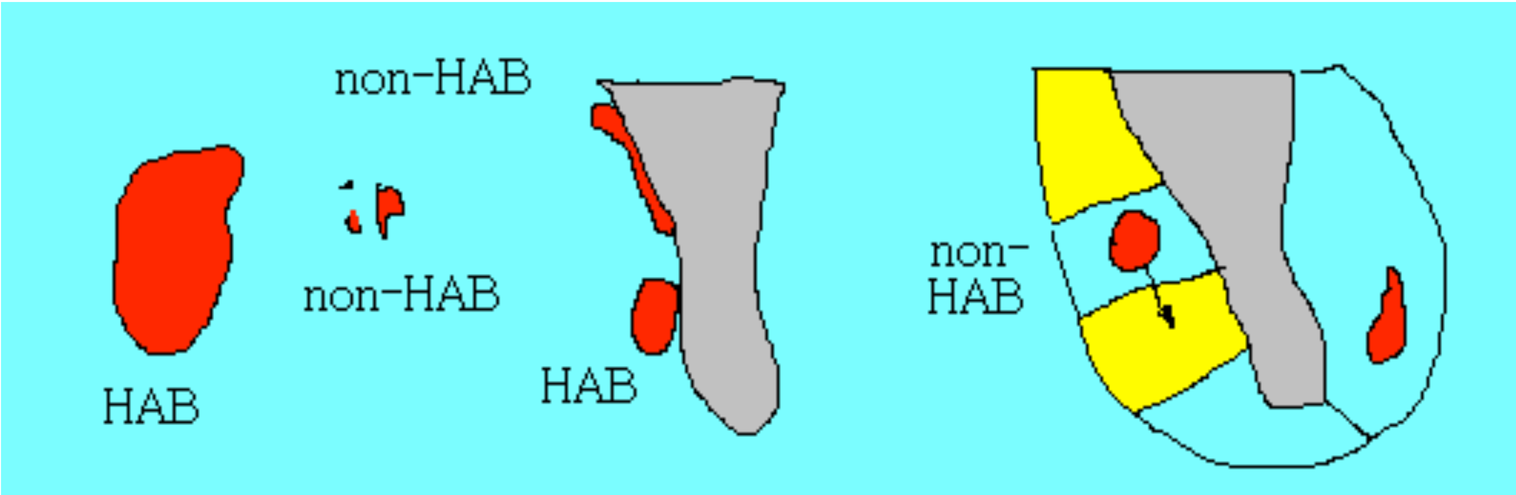


The cloud noise is removed

- probability based
- physical model based

Heuristics for Monitoring HAB

Scientists use visual cues, e.g. size, shape and location, to monitor HAB.



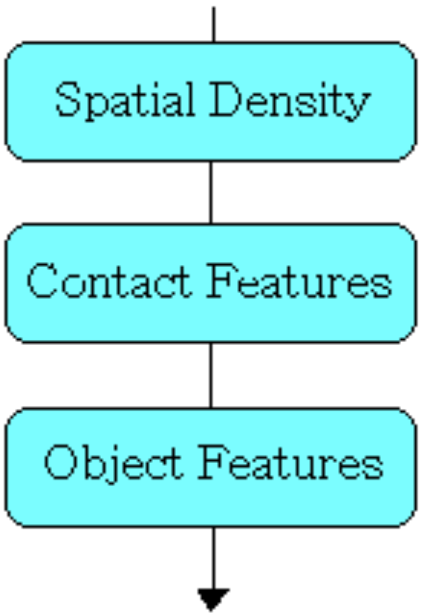
- ***Size:*** **If the anomaly is too small then it's not a HAB.**

- ***Shape:*** **If it is a resuspension anomaly, then it is not a HAB (unless a HAB was previously identified.) If the anomaly extends a long distance along the coast (with coast parallel shape) .**

- ***Region:*** **If a lump develops in the anomaly field, then it is checked by field data for potential HAB. Check "non-HAB" for chlorophyll lumpiness (areas within the anomaly where the chlorophyll peaks).**

Spatial Interaction Filters

- Visual cues are important to monitoring ocean objects.
- We designed filters to code the spatial object interactions.

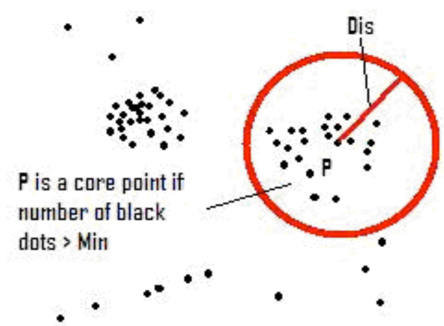


Multilevel Spatial Density Clustering

Contact Area Index (CAI number)

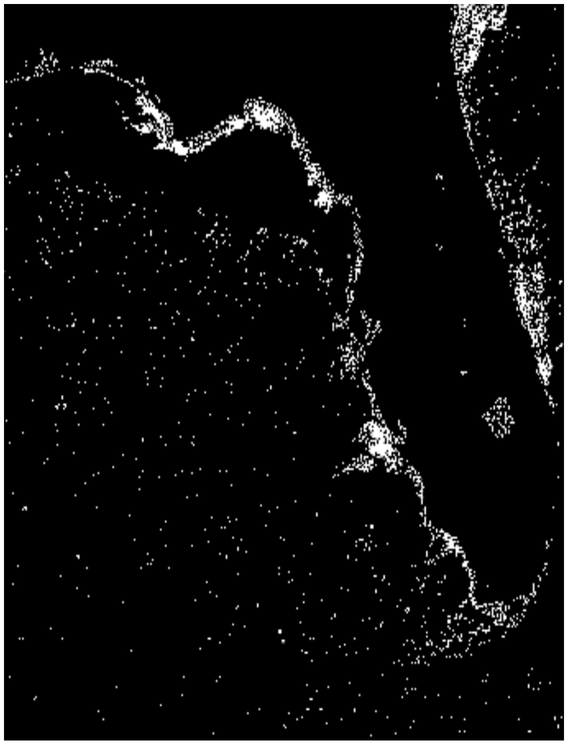
Shape Correlation and Particle Filter

Spatial Density Clustering

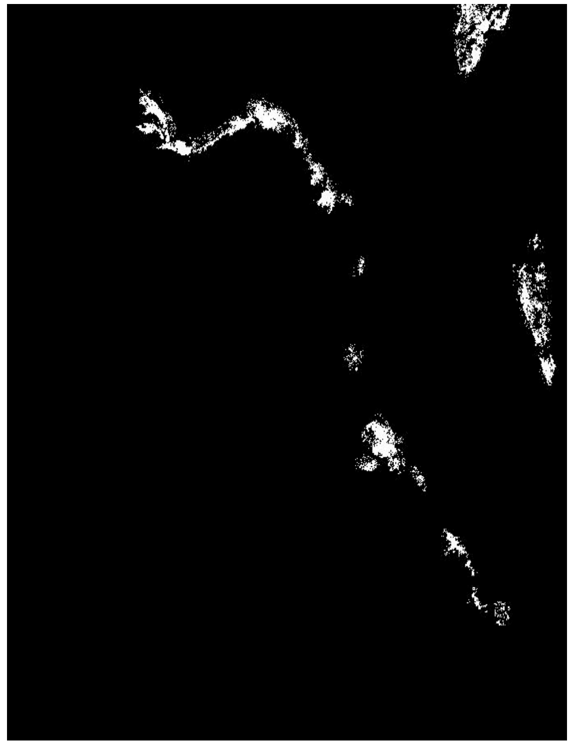


1. Set all the neighboring points within *Dis* as one test set
2. Check spatial density *Min/Dis* for the core points
3. Remove the non-core points
4. Go to step 1

Sample of SDC vs. Binary Morphology



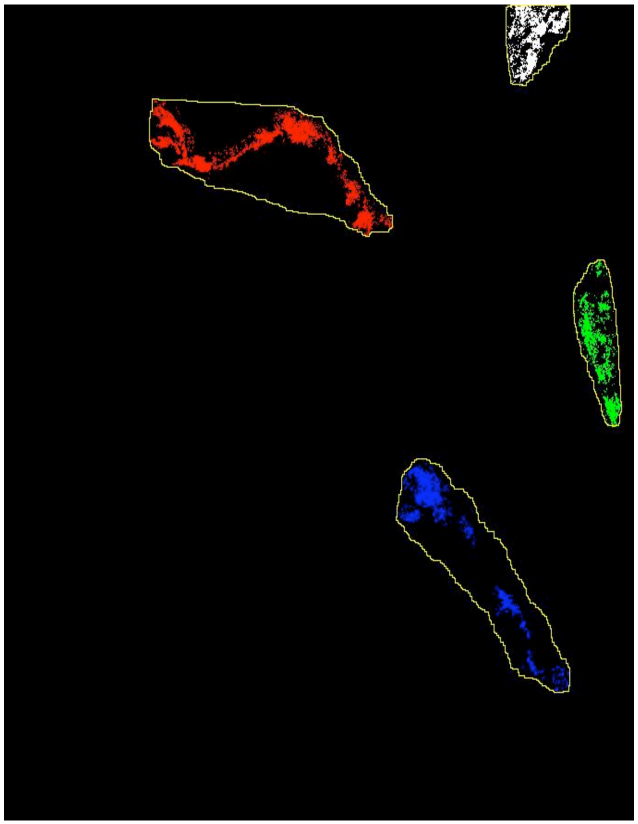
noisy image



SDC output

Morphology output

Active Contour for Grouping

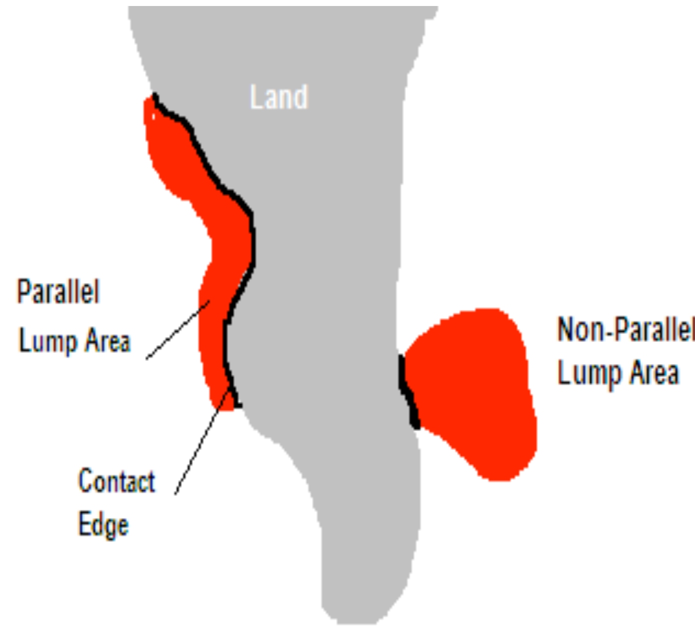


Active Contour outlines 'lumps.'

```
 // active contour for shape outline
   Snake :=
BoundingBox.generate(BoundingBoxCoordinates);
   For each iteration of contour searches
      For each pixel in Snake
         X.new = X.old + α (0.5(X.left + X.right) - X.old)
         Y.new = Y.old + α (0.5(Y.left + Y.right) - Y.old)
         // A pixel stops shrinking when it hits the target
         If PixelSet(X.new, Y.new) not ε target
            X = X.new
            Y = Y.new
         End If
      End For
   End For
   PixelSet.add(Snake);
End
```

Contact Features: Contact Area Index (CAI)

To determine whether a lump area is parallel to the coast line, we created a Contact Area Index (CAI) criterion:



CAI = A / L

A = Area of object [a]
L = Length of contacted edge between object [a] and [b]

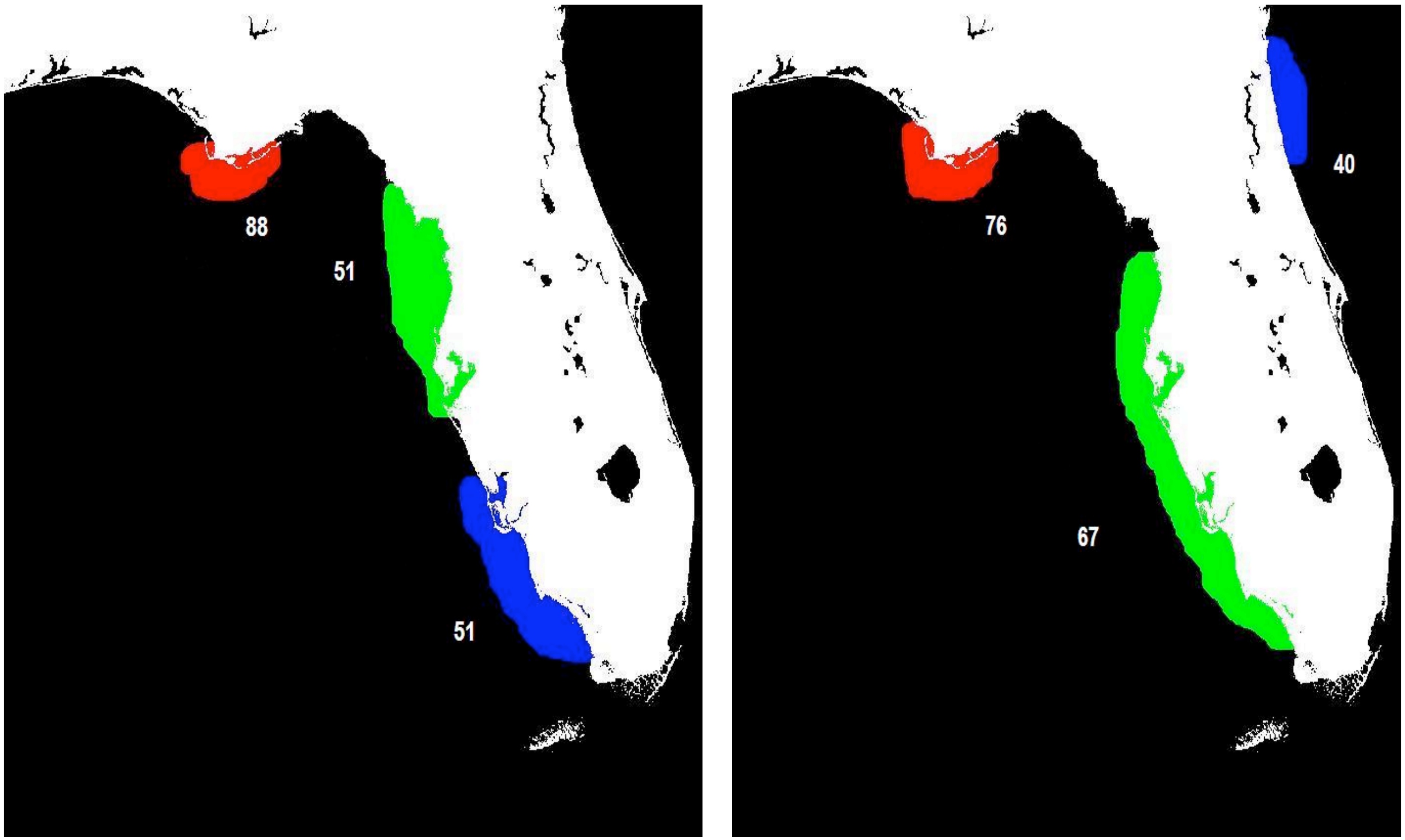
The smaller the CAI number, the more parallelism to the contacted object is.

Algorithm for Computing CAI Number

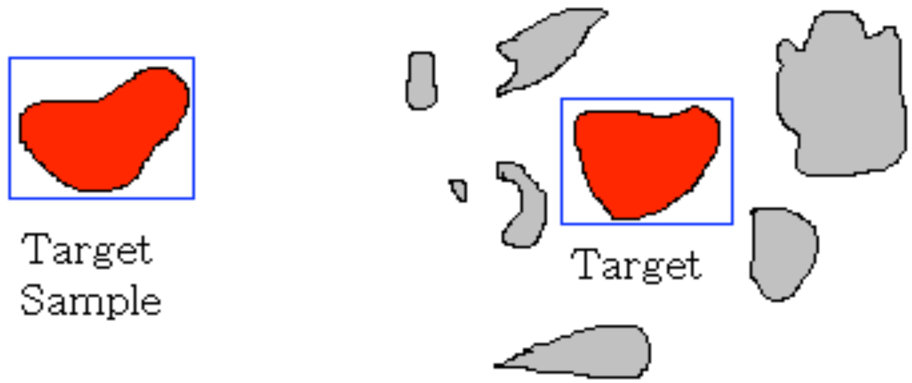
The CAI threshold for determining parallelism of a lump in our project is computed from the training data set. We tested 20 images and found **CAI < 70** could be an initial threshold.

```
img = active contours from snake algorithm;
blooms = imfill(img, 'holes');
blooms = imdilate(img);  // make the blooms touches the coastline
contours = bwperim(blooms);
for each bloom in blooms
  area = 0;
  contactLength = 0;
  for each pixel i of bloom
    area++;
    if contours(i) == 1 // this pixel lies on the boundary
      if land(i) == 1  // overlap with the land
        contactLength++;
      end
    end
  end
  if contactLength != 0
    CAI = area/contactLength;
  else
    CAI = -1;  // it is too far away from coastline
  end
end
```

Sample of Output



Spatial Tracking with Correlation Filter



Shape Correlation = IFFT(FFT(a).* conj(FFT(b)))

where,

a is the test image

b is the reference object in the previous image to be tracked.

FFT(x) represent Discrete Fast Fourier Transform

IFFT(x) is Inverse Discrete Fast Fourier Transform.

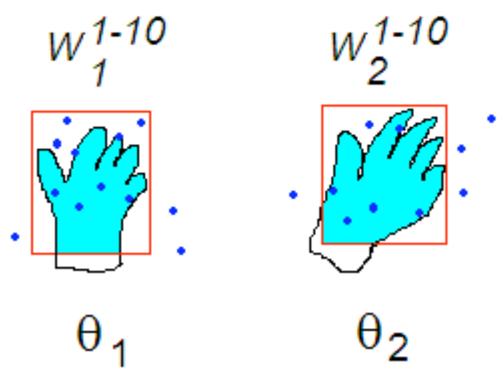
Spatial Tracking with Particle Filter

Given: State transition model : $\theta_t = F_t(\theta_{t-1}, U_t)$

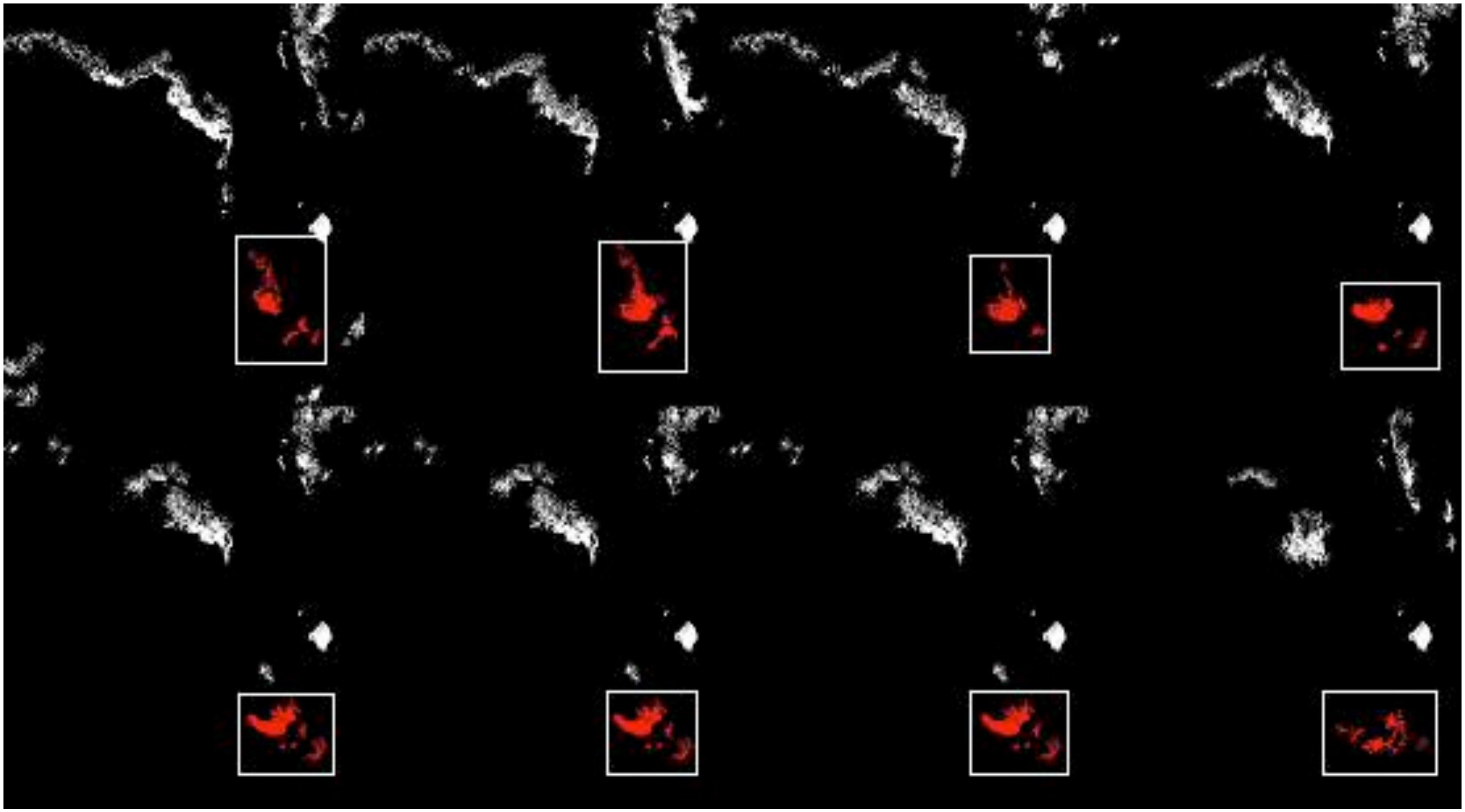
Observation model : $Y_t = G_t(\theta_t, V_t)$

Use a set of particle to estimate the next distribution:

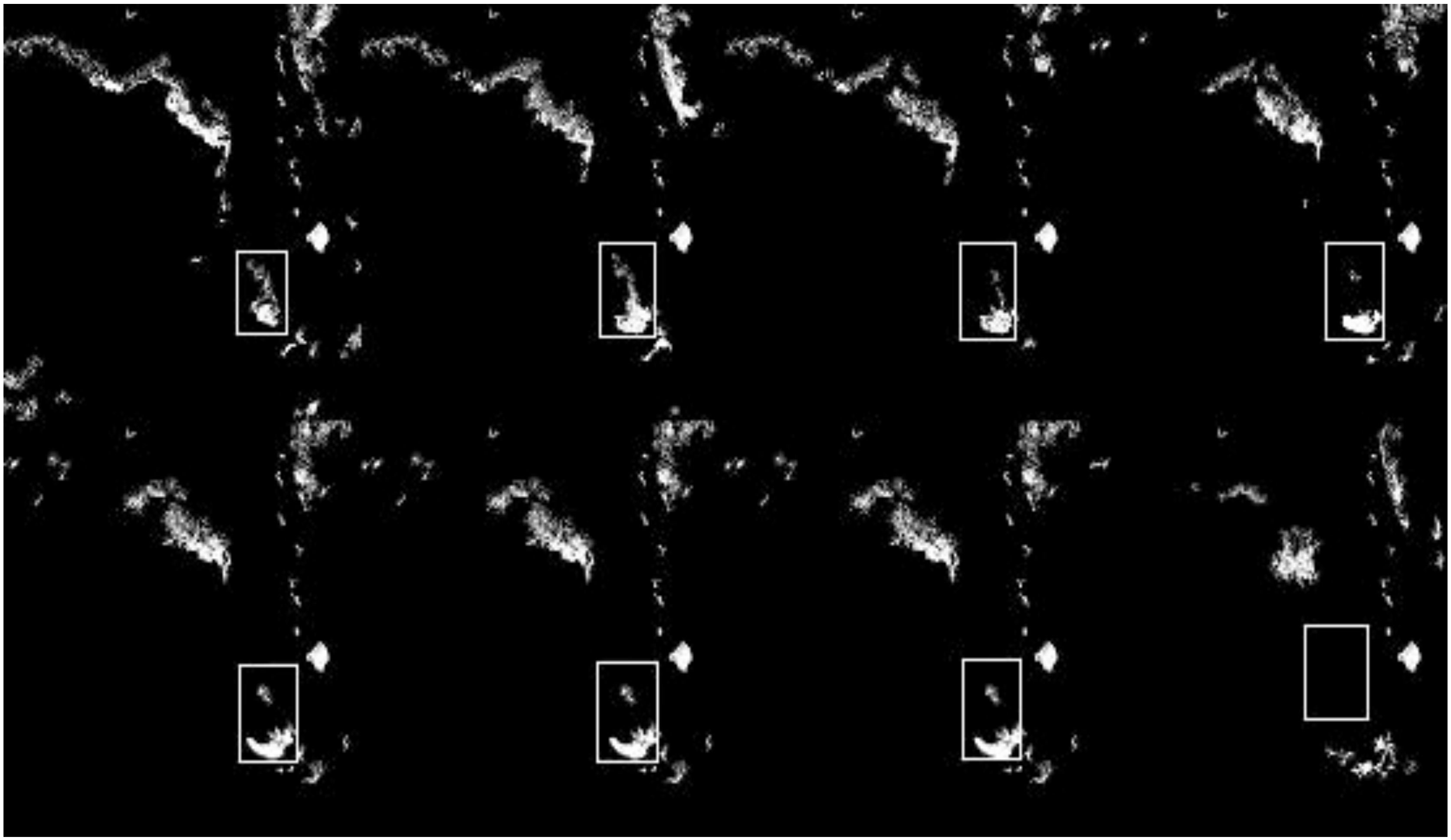
$$\hat{\theta}_t = E[\theta_t | Y_{1:t}] \approx J^{-1} \sum_{j=1}^{J} w_t^{(j)} \theta_t^{(j)}$$



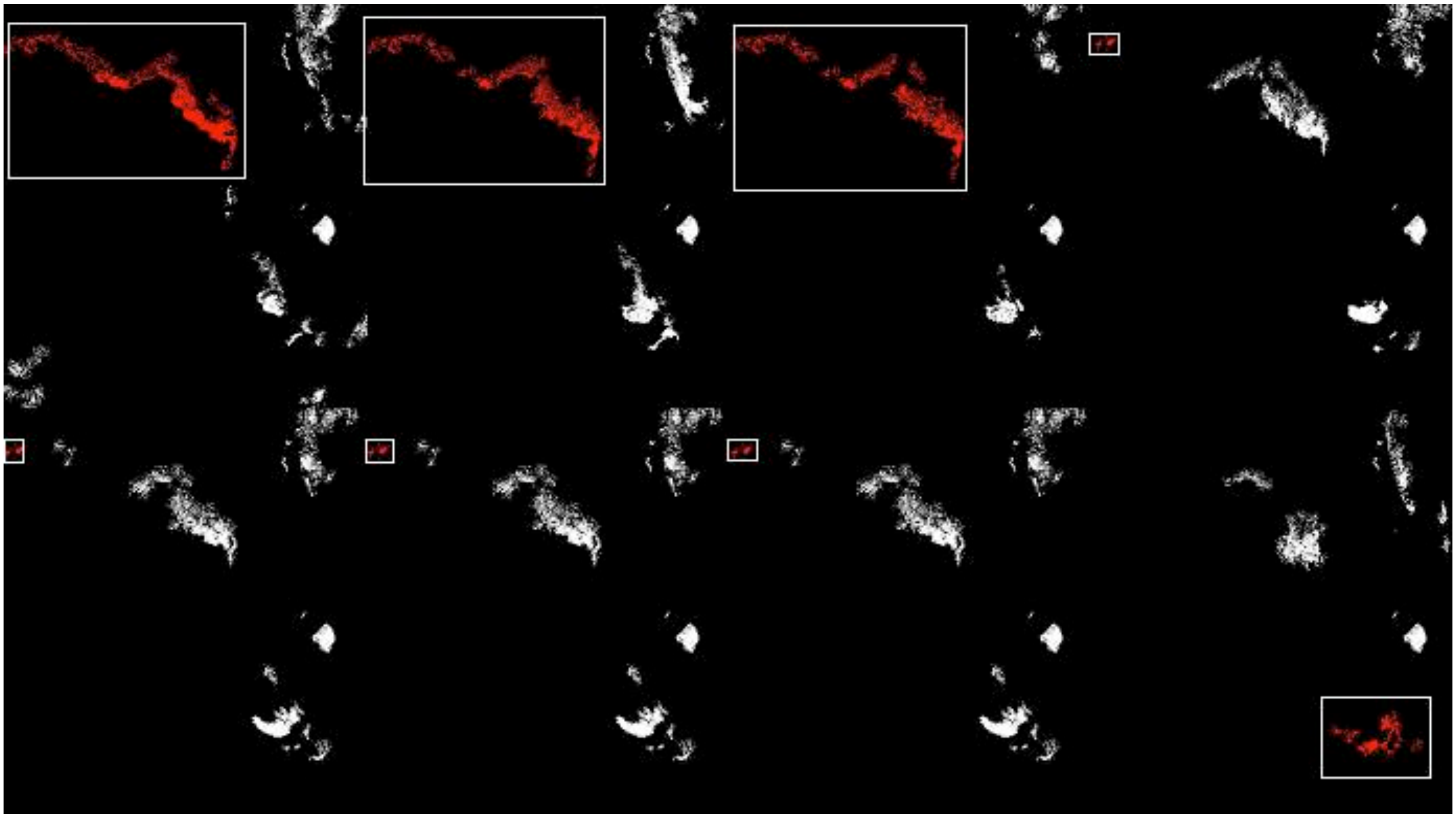
Tracking HAB with Correlation Filter within 4-day interval



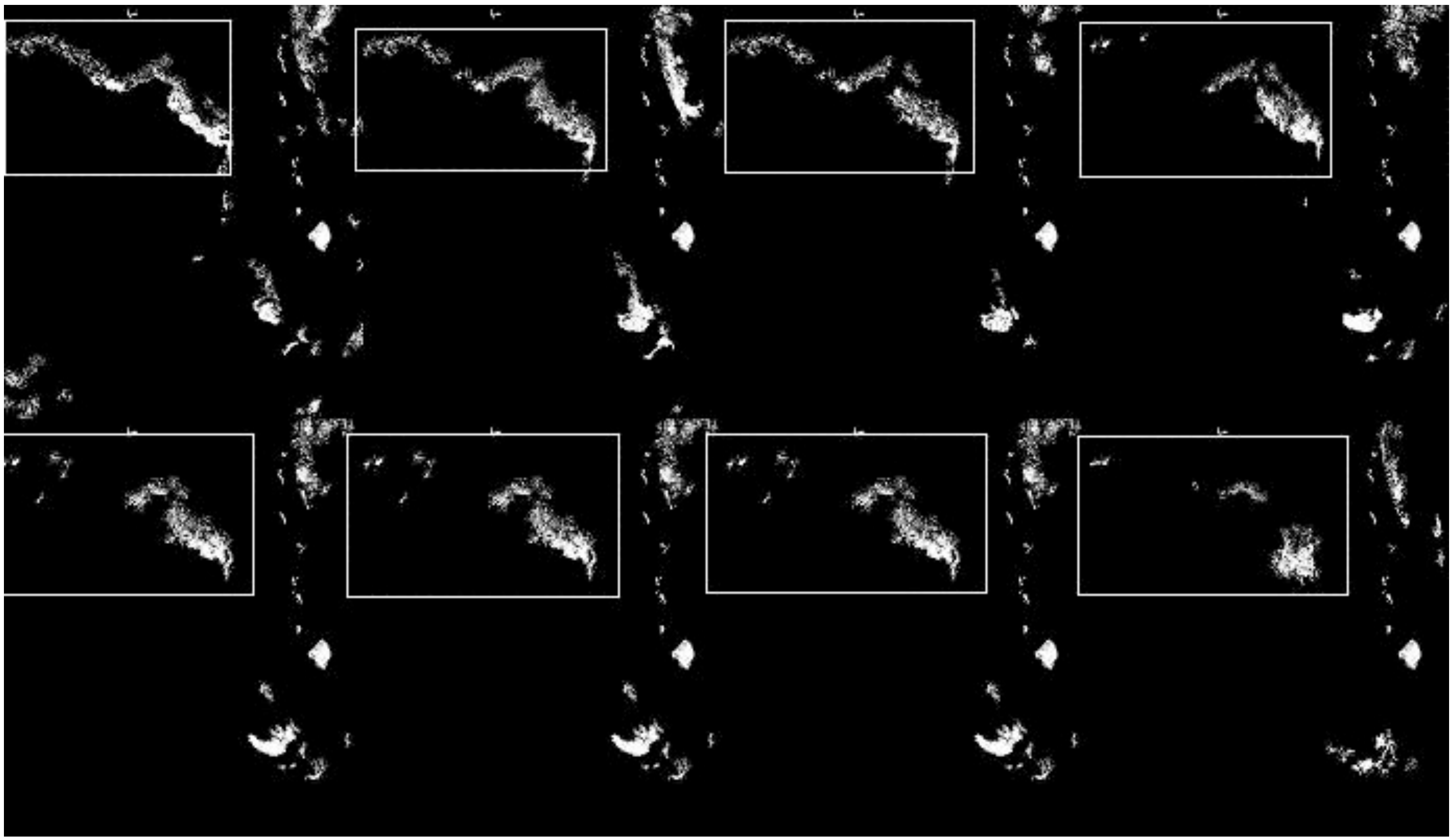
Tracking a bloom with Particle Filter within 4-day interval



Tracking of a bloom which has split into 2 pieces sampled in an interval of 4 days using Correlation Filter



Tracking of a bloom which has split into 2 pieces sampled in an interval of 4 days using particle filter



Results

Case	With Correlation Filter	With Particle Filter
acceptable % for target totally located	79/79 = 100%	40/79 = 50%
acceptable % for target split to two pieces	48/79 = 60%	79/79 = 100%

Preliminary Findings

1. Spatial Density Clustering is an effective way to remove the artifacts in the data.
2. Correlation filter shows robustness in tracking a coherent object. But it is weak in tracking the object that breaks into pieces. Particle filter shows better performance in this case.
3. For better tracking results, it’s necessary to combine oceanographic knowledge with computational algorithms.

References

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